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CIS 4130
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11 September, 2024

Proposal: Analysis of New York City Taxi Trip Data (2020 - 2023)

Dataset Description:
For this project, I propose using the New York City Taxi Trip dataset, a free and open-source collection provided by the NYC Taxi and Limousine Commission (TLC). The dataset contains records of millions of taxi trips in New York City from 2010 to 2020, covering various trip attributes, including pick-up and drop-off times/locations, trip distance, fare amount, and payment method. The dataset has been extensively used in research projects focused on urban mobility and transportation analysis.

URL/Location for Downloading the Data:
The dataset is hosted on the NYC TLC website and can also be accessed through Google BigQuery. The dataset is available as CSV files, with a total size exceeding 50 GB.

Dataset Attributes (Columns):
The key columns include:

- **VendorID**: Taxi company code.
- **Pickup_datetime**: Start time of the trip.
- **Dropoff_datetime**: End time of the trip.
- **Passenger_count**: Number of passengers.
- **Trip_distance**: Distance traveled (miles).
- **RateCodeID**: Rate type for the trip.
- **Pickup_longitude**/**Pickup_latitude**: Pickup GPS coordinates.
- **Dropoff_longitude**/**Dropoff_latitude**: Drop-off GPS coordinates.
- **Payment_type**: Payment method used.
- **Fare_amount**: Fare charged for the trip.
- **Tip_amount**: Tip provided.
- **Total_amount**: Total trip cost (including surcharges).

Objective and Prediction Plan:
The goal of this project is to predict the amount of the tip based on trip attributes such as distance, passenger count, and pickup/drop-off locations. Using regression models, I will forecast the total tip amount. I plan to start with a linear regression model to explore potential relationships between variables. If the linear model does not perform well, I will experiment with advanced techniques like random forests or gradient boosting to capture more complex interactions and non-linearities in the data.

Impact:
Accurate tip predictions can improve fare estimation tools for customers and optimize route

planning for drivers. Insights from the model could also inform transportation policies and urban mobility analysis, identifying patterns in taxi usage and the effects of external factors such as weather and time of day.

Project Milestone 2

Created Google Cloud Storage Bucket:

- Bucket Name: **my-bigdata-project-aa**
- Folder: **/landing** for storing downloaded files.

Data Scraping Process:

- Used requests library to scrape trip data from a government website: https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page.
- Downloaded .parquet files for the years 2020-2023, iterating through months.

```
import requests

Headers = {'user-agent': 'Mozilla/4.0 (compatible; MSIE 5.5; Windows NT)'}

base_url = 'https://d37ci6vzurychx.cloudfront.net/trip-data/'


years_list = ['2020', '2021', '2022', '2023']

month_list = ['01','02','03', '04', '05', '06', '07', '08','09', '10', '11', '12']


for year in years_list:

    for m in month_list:

        file_name = f"fhvhv_tripdata_{year}-{m}.parquet"

        full_url = base_url + file_name

        with open(file_name, 'wb') as outfile:

            response = requests.get(full_url, headers=Headers)
```

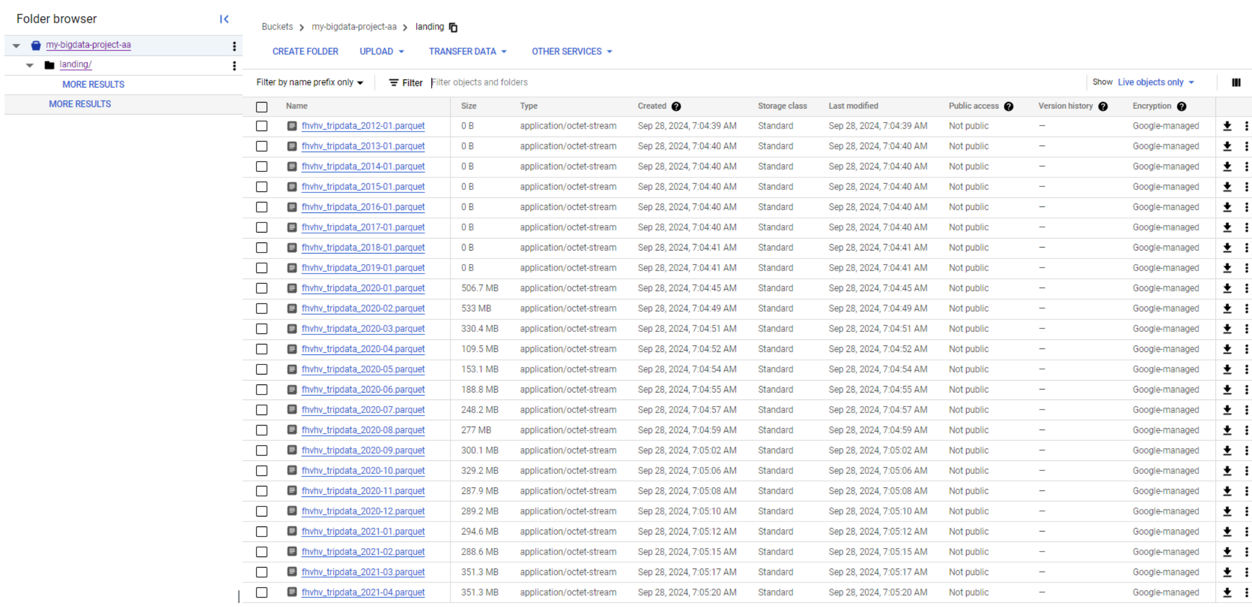
if response.ok:

outfile.write(response.content)

File Transfer to Bucket:

Used gcloud auth list and ls -l to gain permissions.
Moved .parquet files to the bucket's /landing folder using this code:

gsutil mv *.parquet gs://my-bigdata-project-aa/landing/



Folder browser
my-bigdata-project-aa
landing/
MORE RESULTS
MORE RESULTS

Buckets > my-bigdata-project-aa > landing

CREATE FOLDER UPLOAD TRANSFER DATA OTHER SERVICES

Filter by name prefix only Filter Filter objects and folders Show Live objects only

Name	Size	Type	Created	Storage class	Last modified	Public access	Version history	Encryption
fhvhv_tripdata_2012-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:39 AM	Standard	Sep 28, 2024, 7:04:39 AM	Not public	–	Google-managed
fhvhv_tripdata_2013-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:40 AM	Standard	Sep 28, 2024, 7:04:40 AM	Not public	–	Google-managed
fhvhv_tripdata_2014-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:40 AM	Standard	Sep 28, 2024, 7:04:40 AM	Not public	–	Google-managed
fhvhv_tripdata_2015-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:40 AM	Standard	Sep 28, 2024, 7:04:40 AM	Not public	–	Google-managed
fhvhv_tripdata_2016-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:40 AM	Standard	Sep 28, 2024, 7:04:40 AM	Not public	–	Google-managed
fhvhv_tripdata_2017-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:40 AM	Standard	Sep 28, 2024, 7:04:40 AM	Not public	–	Google-managed
fhvhv_tripdata_2018-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:41 AM	Standard	Sep 28, 2024, 7:04:41 AM	Not public	–	Google-managed
fhvhv_tripdata_2019-01.parquet	0 B	application/octet-stream	Sep 28, 2024, 7:04:41 AM	Standard	Sep 28, 2024, 7:04:41 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-01.parquet	506.7 MB	application/octet-stream	Sep 28, 2024, 7:04:45 AM	Standard	Sep 28, 2024, 7:04:45 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-02.parquet	533 MB	application/octet-stream	Sep 28, 2024, 7:04:49 AM	Standard	Sep 28, 2024, 7:04:49 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-03.parquet	330.4 MB	application/octet-stream	Sep 28, 2024, 7:04:51 AM	Standard	Sep 28, 2024, 7:04:51 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-04.parquet	109.5 MB	application/octet-stream	Sep 28, 2024, 7:04:52 AM	Standard	Sep 28, 2024, 7:04:52 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-05.parquet	153.1 MB	application/octet-stream	Sep 28, 2024, 7:04:54 AM	Standard	Sep 28, 2024, 7:04:54 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-06.parquet	188.8 MB	application/octet-stream	Sep 28, 2024, 7:04:55 AM	Standard	Sep 28, 2024, 7:04:55 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-07.parquet	248.2 MB	application/octet-stream	Sep 28, 2024, 7:04:57 AM	Standard	Sep 28, 2024, 7:04:57 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-08.parquet	277 MB	application/octet-stream	Sep 28, 2024, 7:04:59 AM	Standard	Sep 28, 2024, 7:04:59 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-09.parquet	300.1 MB	application/octet-stream	Sep 28, 2024, 7:05:02 AM	Standard	Sep 28, 2024, 7:05:02 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-10.parquet	329.2 MB	application/octet-stream	Sep 28, 2024, 7:05:06 AM	Standard	Sep 28, 2024, 7:05:06 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-11.parquet	287.9 MB	application/octet-stream	Sep 28, 2024, 7:05:08 AM	Standard	Sep 28, 2024, 7:05:08 AM	Not public	–	Google-managed
fhvhv_tripdata_2020-12.parquet	289.2 MB	application/octet-stream	Sep 28, 2024, 7:05:10 AM	Standard	Sep 28, 2024, 7:05:10 AM	Not public	–	Google-managed
fhvhv_tripdata_2021-01.parquet	294.6 MB	application/octet-stream	Sep 28, 2024, 7:05:12 AM	Standard	Sep 28, 2024, 7:05:12 AM	Not public	–	Google-managed
fhvhv_tripdata_2021-02.parquet	288.6 MB	application/octet-stream	Sep 28, 2024, 7:05:15 AM	Standard	Sep 28, 2024, 7:05:15 AM	Not public	–	Google-managed
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fhvhv_tripdata_2021-04.parquet	351.3 MB	application/octet-stream	Sep 28, 2024, 7:05:20 AM	Standard	Sep 28, 2024, 7:05:20 AM	Not public	–	Google-managed

Project Milestone 3

EDA Objectives

The goal of the Exploratory Data Analysis (EDA) was to gain a better understanding of the dataset by visualizing key patterns and identifying relationships between variables. This helped in detecting potential issues and outliers that could inform the data cleaning process.

Key steps:

1. Descriptive Statistics: Calculated summary statistics such as mean, median, and standard deviation to understand the data distribution.
2. Data Visualizations:

    - Histogram for Trip Distance: Showed how trip distances are distributed across the dataset.
    - Scatter Plot for Fare Amount vs. Trip Distance: Illustrated the relationship between trip length and fare cost, highlighting trends and anomalies.
    - Correlation Heatmap: Visualized correlations between numeric variables to identify strong relationships or unexpected patterns.

EDA Findings:

- Trip Distance: The majority of trips were short, with a sharp decline for longer distances, suggesting typical urban travel patterns.
- Fare Patterns: There was a clear, positive relationship between trip distance and fare amount, with longer trips generally costing more. However, some anomalies suggested inconsistent pricing.
- Correlations: Strong correlations were found between fare-related variables, such as fare_amount, extra, and tip_amount. The heatmap helped in identifying factors that affect fare prices.

Data Cleaning

Cleaning Objectives:

- Removing or imputing missing values.
- Ensuring consistent data types.
- Renaming columns for clarity and standardization.
- Dropping unnecessary columns.

Implementation:

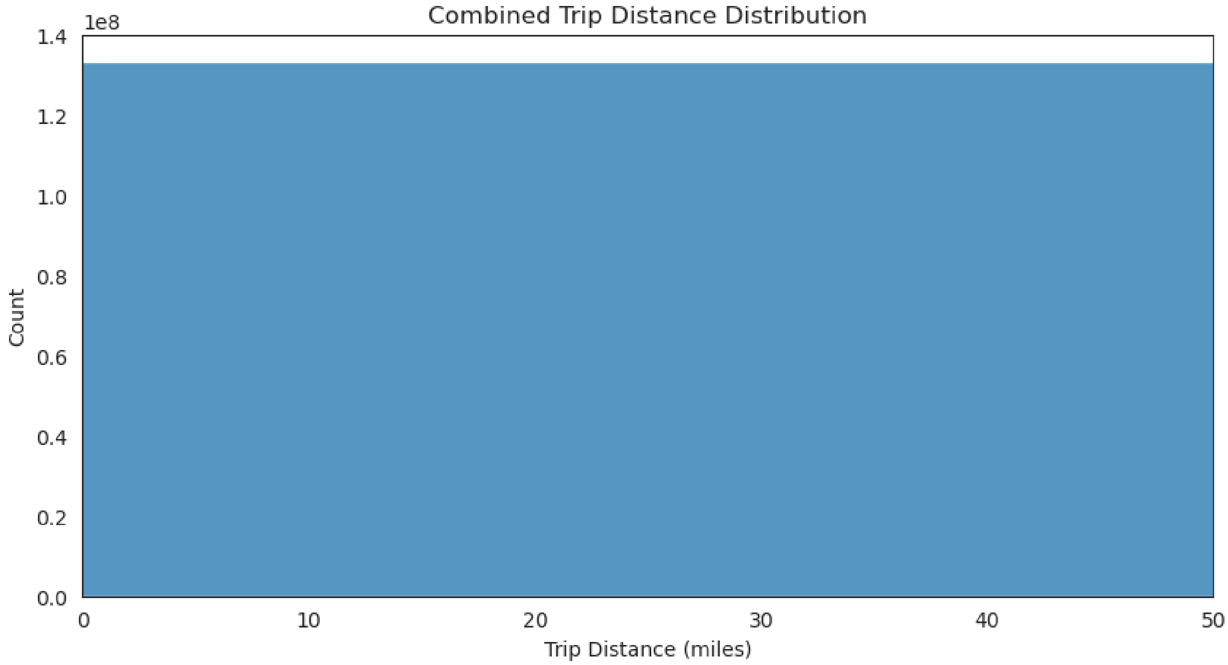
Python libraries such as Pandas were used to automate the cleaning process. This allowed for efficient handling of large datasets and ensured that the cleaning procedures were reproducible and scalable.

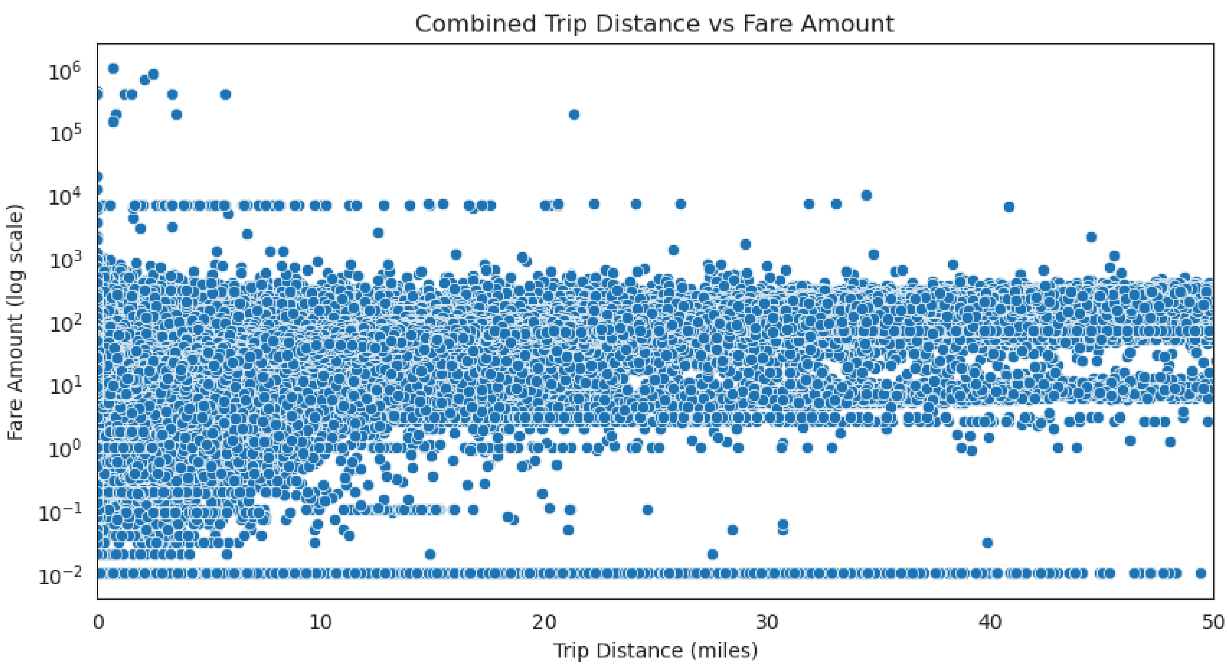
Results and Conclusion

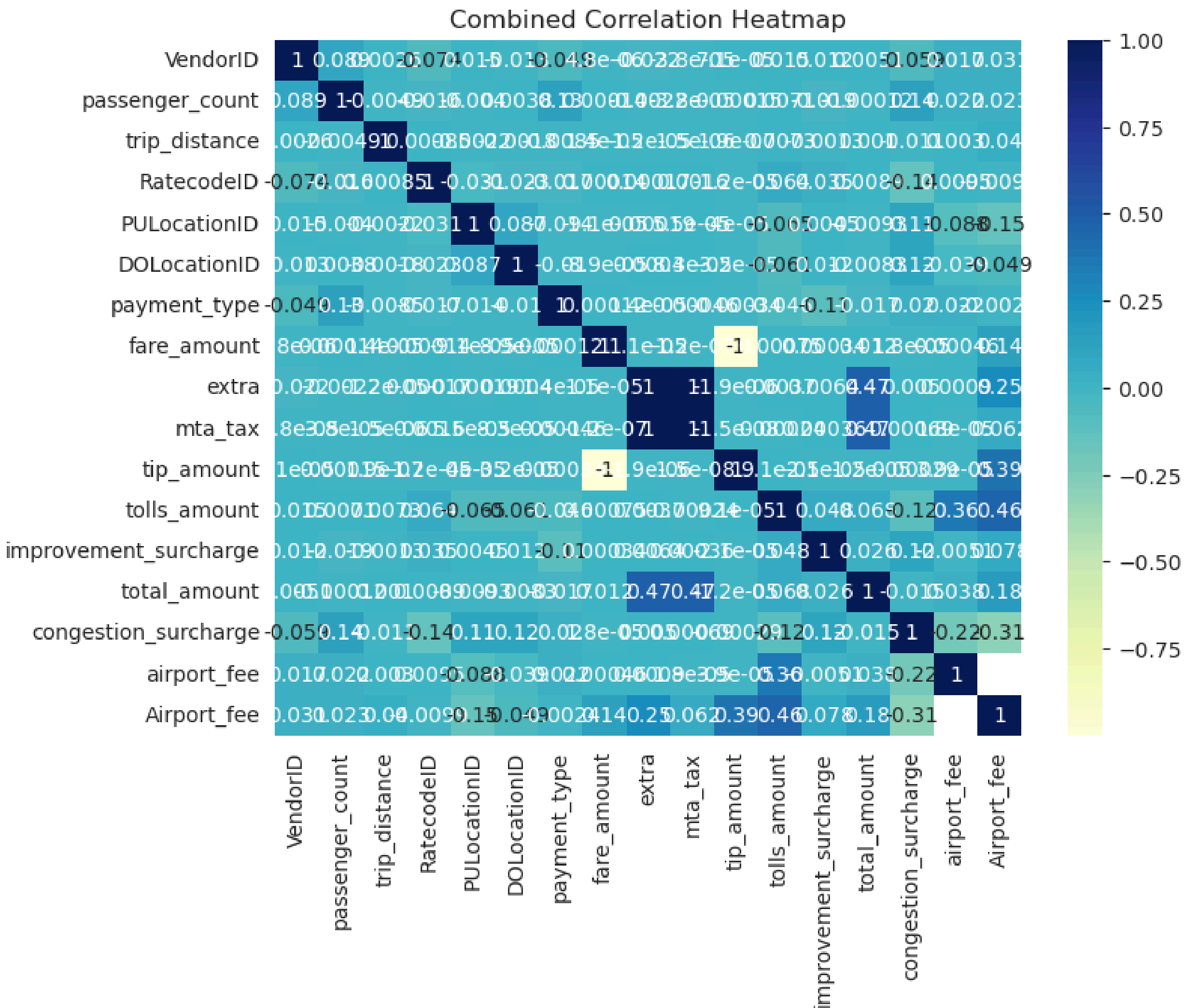
Key Achievements:

- Consistent, Clean Dataset: The data was cleaned, standardized, and made consistent across all fields, enabling more reliable analysis.
- Automation: Automated the cleaning and processing tasks, making it easier to handle multiple files and future data additions.

- Initial Insights through EDA: The EDA process helped identify trends, patterns, and anomalies, providing a basis for more detailed future analysis.







Summary and Challenges in Feature Engineering

The dataset consists of trip records from 2020 to 2023, capturing attributes such as pickup, dropoff times, trip distance, fare details, and other relevant features like payment type, passenger count, and location IDs. The primary goal of the data cleaning process was to standardize this information by handling missing values, dropping unnecessary columns, and ensuring consistent naming across all attributes.

Feature engineering for this dataset presents a few challenges. One potential issue is the handling of outliers, such as extremely high or low fare amounts, distances, or unusual pickup and dropoff times. Additionally, converting categorical data like payment types into meaningful numerical features which may require careful encoding, especially if some values appear sporadically throughout the dataset. Another challenge will be the temporal features, like rush hour vs. off-peak or weekdays vs. weekends which can require additional time-based transformations. We will need to be cautious to avoid data leakage when creating features that might use information not available at prediction time.

During the feature engineering phase, I will have to carefully consider what will be needed to handle these complexities to ensure that the derived features are both informative and robust, leading to better model performance.

Project Milestone 4

Purpose of the model: My model is designed to predict the tip amount for taxi rides based on various trip characteristics, such as trip distance, base fare, tolls, congestion surcharge, and temporal factors like pickup time and day of the week. The goal is to provide accurate predictions that can help analyze tipping behavior, optimize pricing strategies, and improve decision-making in the ride-hailing industry.

Col name	Data type	Feature engineering treatment
trip_miles	Double	numeric feature
tolls	Double	numeric feature
sales_tax	Double	numeric feature
congestion_surcharge	Double	numeric feature
airport_fee	Double	numeric feature
log_fare	Double	Log transformation of base_passenger_fee
trip_duration	Double	Scaled using VectorAssembler
pickup_hour	Integer	Extracted hour from pickup_datetime.
pickup_day	Integer	Extracted day of the week from pickup_datetime
pickup_month	Integer	Extracted month from pickup_datetime

Code Description

1. Reading Cleaned Data and Processing

- The cleaned data is read from the /cleaned folder using the SparkSession.

- Feature engineering is performed to derive trip_duration as a critical input feature.

2. Feature Engineering

Feature engineering is performed using the feature_engineering function. The following transformations are applied:

Calculate Trip Duration:

- The duration of each trip is calculated by taking the difference between dropoff_datetime and pickup_datetime using unix_timestamp.
- The original timestamp columns are dropped to save memory and streamline processing.
- A VectorAssembler combines input columns into a single feature vector for the model.
- The chosen columns (trip_miles, tolls, sales_tax, congestion_surcharge, trip_duration) represent key aspects of a trip that may influence the tip amount.

3. Train/Test Split

- Data is split into training and testing subsets for model building and evaluation.
- Utilized randomSplit which divides the data into 80% for training and 20% for testing.

4. Modeling

Linear Regression from PySpark's MLlib library is used for its simplicity and interpretability.

The model predicts tips (the target variable) using the combined feature vector (features).

A regularization parameter (regParam=0.01) is set to prevent overfitting.

5. Validation and Evaluation

The trained model is validated using:

- **Mean Squared Error (MSE):** Measures the average squared difference between actual and predicted tips.

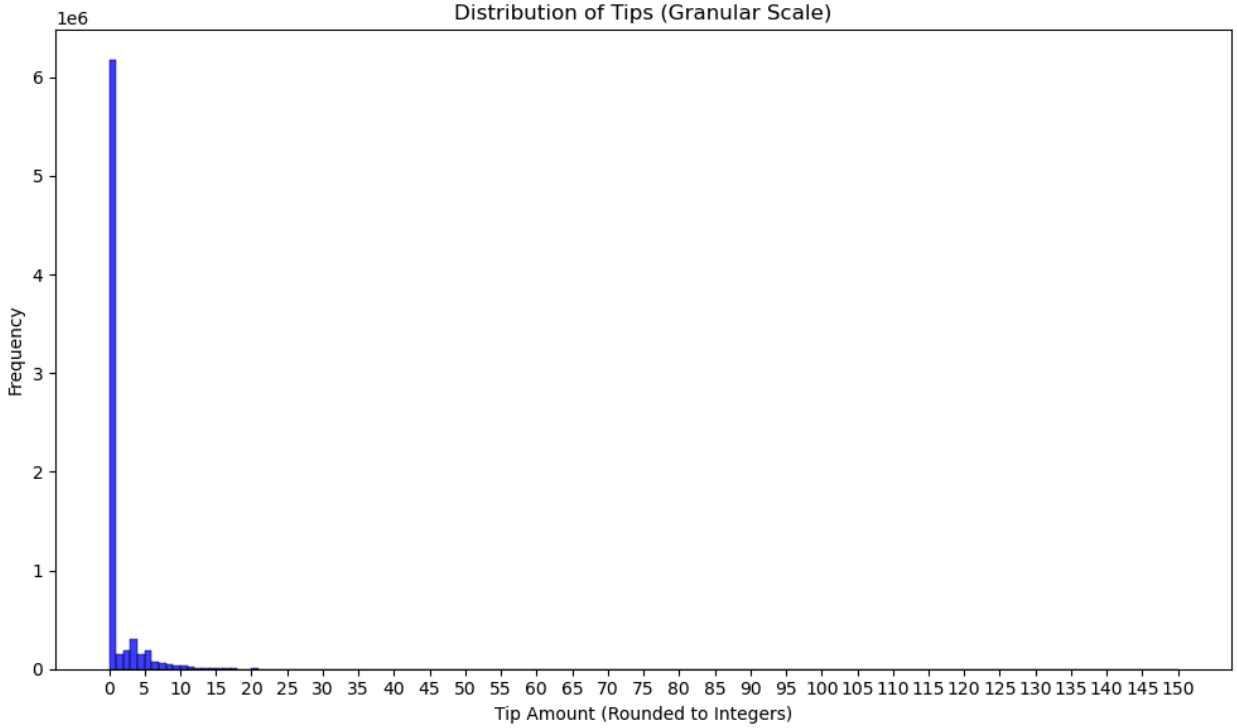
- **Mean Absolute Error (MAE):** Calculates the average absolute difference between actual and predicted tips.
- **R-squared (R^2):** Indicates how well the model explains variance in the data (closer to 1 is better).

6. Saving Outputs

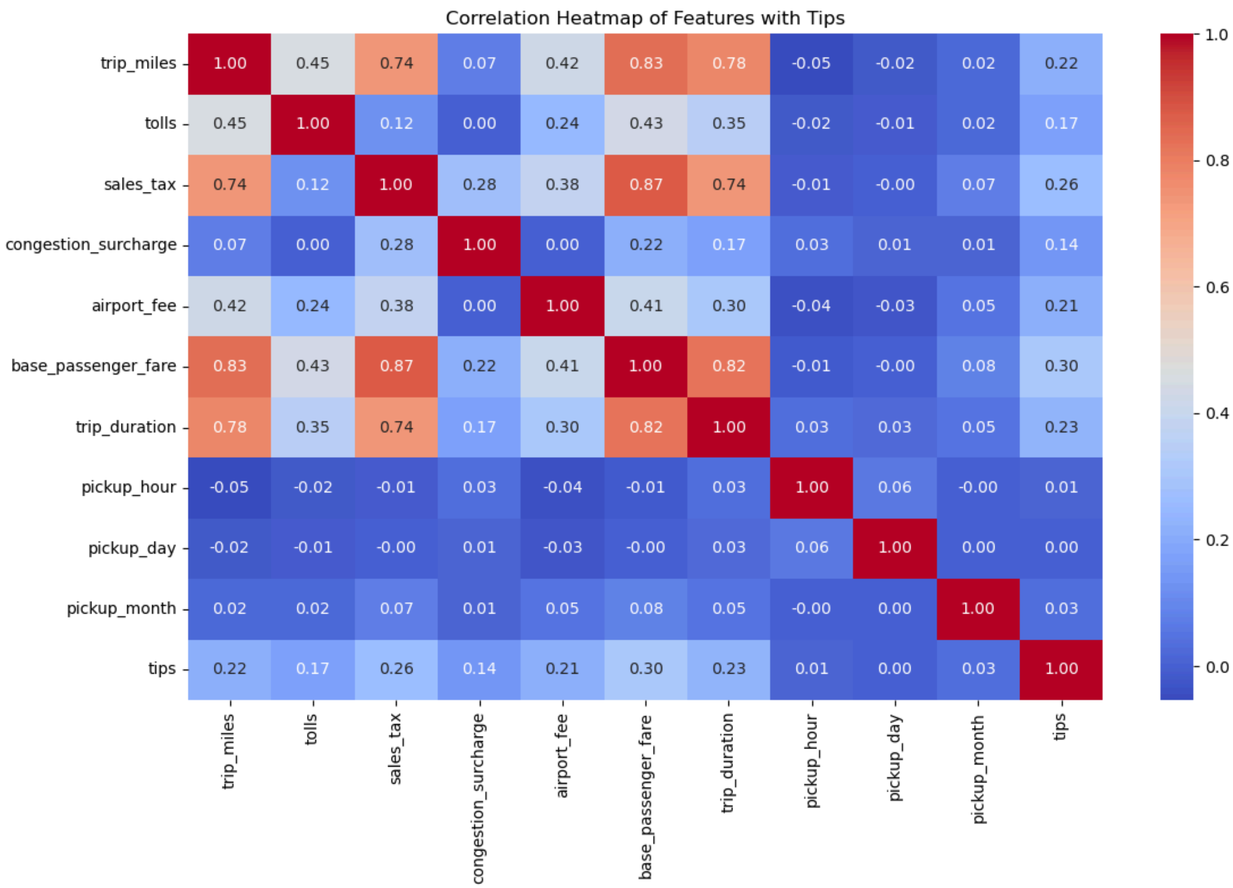
- Feature-Engineered Data: Processed data for each month is saved to the /trusted folder in Parquet format.
- Trained Models: The trained model is saved to the /models folder in the bucket.

Project Milestone 5

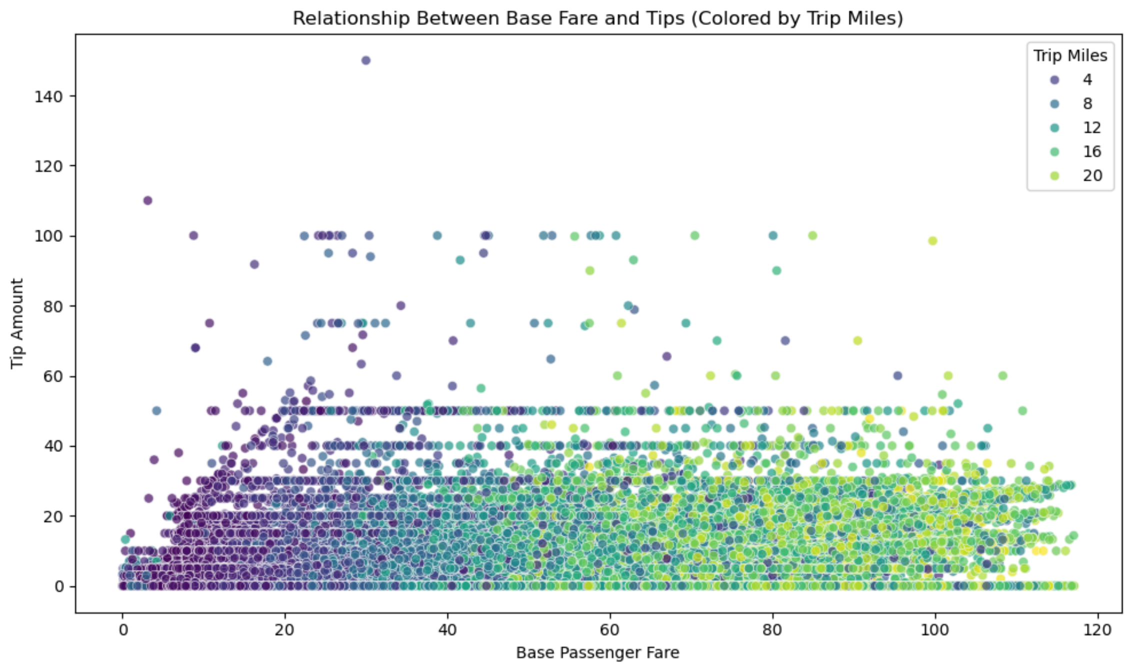
1) Visualizations and importance:



This histogram visualizes the frequency of different tip amounts. It demonstrates that most tips fall within a low range, with only a few instances of high tips. The granularity allows us to identify exact tipping trends, which can inform pricing strategies or customer behavior analysis.

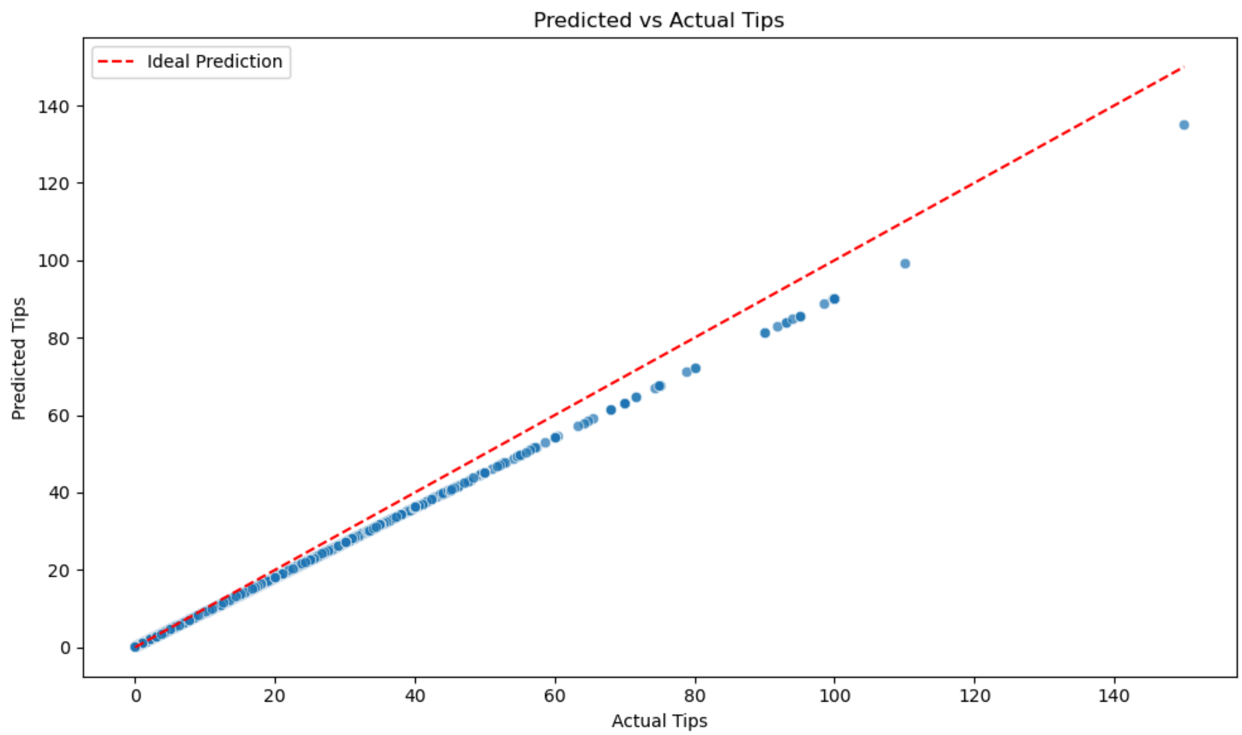


This heatmap shows the correlation between various features and the target variable, `tips`. The strongest correlation is observed with `base_passenger_fare`, indicating it has the highest influence on tipping behavior.

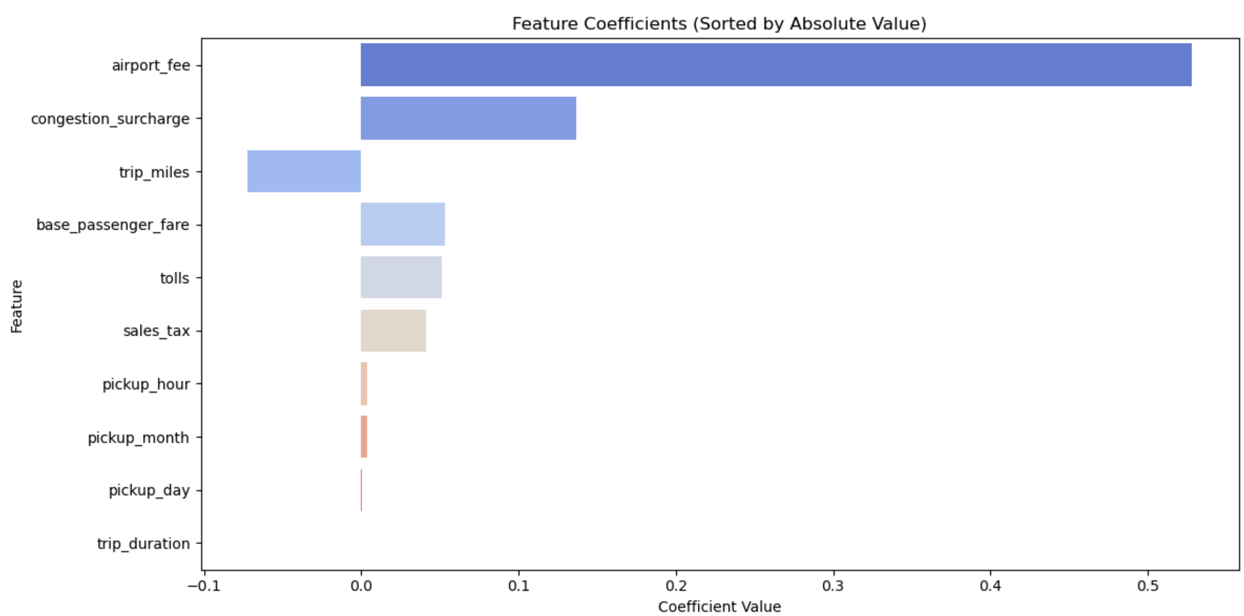


This scatter plot illustrates how tip amounts vary with base fare. Points are colored by trip_miles to add another layer of insight, revealing that higher base fares and longer trips tend to have higher tips.

This boxplot highlights how sales tax levels correspond to tips. It suggests that higher sales tax amounts are associated with slightly higher tips, likely due to proportional tipping practices.



This scatter plot compares the actual tip amounts (from the dataset) against the predicted tip amounts (from the model). Each point represents a single trip. The red dashed line serves as an ideal prediction line, where predicted tips perfectly match the actual tips.



This bar graph ranks the importance of features based on their model coefficients (absolute values). Features with higher coefficients have a larger influence on the predicted tips, either positively or negatively.

2) Identify Important Features:

Airport Fee (Coefficient: 0.528): Highly correlated with tips and strongly influences the prediction.

Congestion Surcharge (Coefficient: 0.137): Moderate importance.

Trip Miles (Coefficient: -0.072): Negative contribution but significant.

Project Milestone 6

Project Summary:

This project involved building a data processing and machine learning pipeline to predict taxi trip tips using data from the New York City Taxi and Limousine Commission (TLC). The pipeline was designed to handle large-scale datasets spanning multiple years, preprocess the data, engineer features, and train a machine learning regression model. The end goal was to produce a predictive model capable of estimating tips based on trip characteristics while handling data complexity and providing insights through exploratory analysis and visualizations.

Key Steps in the Data Processing Pipeline

1. **Data Loading and Cleaning:**
- Combined over 50GB of parquet files into a unified dataset.
- Addressed inconsistent data types (e.g., converting airport_fee to double).
- Dropped or adjusted extreme outliers for trip_miles, base_passenger_fare, and tips.
- Ensured all columns were relevant to the analysis and prediction task.

2. **Feature Engineering:**
- Extracted new features from timestamps (e.g., pickup_hour, pickup_day, pickup_month).
- Calculated trip_duration as the difference between pickup and drop-off times.
- Applied log transformations to skewed features (trip_miles and base_passenger_fare).

3. **Exploratory Data Analysis (EDA):**

Visualized key patterns and relationships:

- Distribution of tips showed a highly skewed dataset dominated by $0 tips.
- A correlation heatmap identified important predictors like base_passenger_fare, sales_tax, and trip_miles.
- Scatter plots and box plots highlighted relationships between features and tips.

4. **Model Training and Validation:**

- **Employed a Linear Regression model trained with Cross Validation to ensure robust evaluation.**
- **Identified the most significant features contributing to tips predictions:**
  - **Top Features: airport_fee, congestion_surcharge, and base_passenger_fare.**
- **Evaluated the model's performance:**
  - **Metrics: R^2 = 0.58%, MSE = 5.71, MAE = 1.54.**
  - **The modest R^2 suggests that tips are influenced by unobserved or non-linear factors.**

5. **Data Visualization:**
   - **Created comprehensive visualizations to communicate insights:**
     - **A scatter plot of Predicted vs. Actual Tips highlighted the model's performance.**
     - **A bar graph of Feature Coefficients ranked the importance of predictors.**
     - **Distribution and correlation plots provided an understanding of feature distributions and relationships.**

Appendix B:

EDA Source Code:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns


# Set display options for better readability

pd.set_option('display.float_format', '{:.2f}'.format)

pd.set_option('display.width', 1000)

%matplotlib inline


# Function to load data from multiple files

def load_data(file_paths, file_type='csv'):

    df_list = []

    for file_path in file_paths:

        if file_type == 'csv':

            df = pd.read_csv(file_path)

        elif file_type == 'parquet':

            df = pd.read_parquet(file_path, engine='pyarrow', storage_options={'anon': True})

        elif file_type == 'json':

            df = pd.read_json(file_path, lines=True)

        else:

            raise ValueError("Unsupported file type")


        df_list.append(df)
```

```
    # Concatenate all DataFrames into a single DataFrame
    return pd.concat(df_list, ignore_index=True)

# Function to perform EDA (without visualizations)
def perform_eda(df):
    # Basic Information
    print("Basic Data Info:")
    print(df.info())

    # Descriptive Statistics
    print("\nDescriptive Statistics:")
    print(df.describe())

    # Check for Missing Values
    print("\nMissing Values per Column:")
    print(df.isnull().sum())

    # Replace or Drop Missing Values Example
    df.fillna({'passenger_count': 0, 'RatecodeID': 1, 'congestion_surcharge': 0, 'airport_fee': 0},
inplace=True)
    df.dropna(subset=['fare_amount', 'trip_distance'], inplace=True)

    # Convert to DateTime
    if 'tpep_pickup_datetime' in df.columns and 'tpep_dropoff_datetime' in df.columns:
        df['tpep_pickup_datetime'] = pd.to_datetime(df['tpep_pickup_datetime'])
        df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'])
```

```
    return df

# Function to process data in batches and combine afterward
def process_in_batches_and_combine(file_paths, batch_size=3, file_type='parquet'):
    num_files = len(file_paths)
    batch_results = []

    # Process files in batches
    for i in range(0, num_files, batch_size):
        batch_files = file_paths[i:i + batch_size]
        print(f"Processing batch: {batch_files}")

        # Load and process batch
        df_batch = load_data(batch_files, file_type)
        processed_df = perform_eda(df_batch)

        # Save batch result to a list
        batch_results.append(processed_df)

    # Combine all batches into one final DataFrame
    final_df = pd.concat(batch_results, ignore_index=True)
    return final_df

# Function to generate combined visualizations
def generate_combined_visualizations(df):
    sns.set_style("white")
```

```
# Histogram for Trip Distance

if 'trip_distance' in df.columns:

    plt.figure(figsize=(10, 5))

    sns.histplot(df['trip_distance'], bins=30)

    plt.xlim(0, 50)  # Limit to a reasonable range for better visibility

    plt.title('Combined Trip Distance Distribution')

    plt.xlabel('Trip Distance (miles)')

    plt.show()


# Scatter Plot

if 'fare_amount' in df.columns and 'trip_distance' in df.columns:

    plt.figure(figsize=(10, 5))

    sns.scatterplot(x='trip_distance', y='fare_amount', data=df)

    plt.xlim(0, 50)  # Limit the x-axis to trips less than 50 miles for better scaling

    plt.yscale('log')  # Apply a logarithmic scale to the y-axis

    plt.title('Combined Trip Distance vs Fare Amount')

    plt.xlabel('Trip Distance (miles)')

    plt.ylabel('Fare Amount (log scale)')

    plt.show()


# Correlation Heatmap

numeric_cols = df.select_dtypes(include=['float64', 'int64']).columns

plt.figure(figsize=(8, 6))

sns.heatmap(df[numeric_cols].corr(), annot=True, cmap="YlGnBu")

plt.title('Combined Correlation Heatmap')
```

```
    plt.show()


# Generate file paths for the years 2020 to 2023 in Parquet format
file_paths = [
    f"https://d37ci6vzurychx.cloudfront.net/trip-data/yellow_tripdata_{year}-{str(month).zfill(2)}.parquet"
    for year in range(2020, 2024) for month in range(1, 13)
]
file_type = 'parquet'


# Process data in batches and combine into one final DataFrame
final_df = process_in_batches_and_combine(file_paths, batch_size=3, file_type=file_type)


# Generate combined visualizations after processing all data
generate_combined_visualizations(final_df)
```

Appendix C:

Data Cleaning Code:

```
# Import necessary libraries
import pandas as pd
from google.cloud import storage
import os

# Set up Google Cloud Storage client
client = storage.Client()
bucket_name = "my-bigdata-project-aa"
landing_folder = "landing"
cleaned_folder = "cleaned"

# Function to load data from GCS
def load_data_from_gcs(file_path):
    bucket = client.get_bucket(bucket_name)
    blob = bucket.blob(file_path)
    with blob.open("rb") as file:
        return pd.read_parquet(file)

# Function to clean data
def clean_data(df):
    # Remove spaces from column names and standardize to lowercase
    df.columns = [col.strip().replace(" ", "_").lower() for col in df.columns]

    # Drop unneeded columns
    unneeded_columns = ['store_and_fwd_flag', 'shared_request_flag', 'shared_match_flag',
'access_a_ride_flag']
    df.drop(columns=[col for col in unneeded_columns if col in df.columns], inplace=True, errors='ignore')

    # Fill or drop missing values
    df.fillna({
        'passenger_count': 0,
        'ratecodeid': 1,
        'congestion_surcharge': 0,
        'airport_fee': 0
    }, inplace=True)
    df.dropna(subset=['base_passenger_fare', 'trip_miles'], inplace=True)  # Replace with appropriate
columns

    # Convert data types for efficiency and consistency
    df = df.astype({
```

```
        'hvfhs_license_num': 'category',
        'dispatching_base_num': 'category',
        'pulocationid': 'Int64',
        'dolocationid': 'Int64',
        'trip_miles': 'float',
        'base_passenger_fare': 'float'
    })

    # Remove records with invalid data
    df = df[(df['trip_miles'] > 0) & (df['base_passenger_fare'] > 0)]

    # Handle outliers by capping at the 99th percentile
    if 'base_passenger_fare' in df.columns:
        fare_cap = df['base_passenger_fare'].quantile(0.99)
        df = df[df['base_passenger_fare'] <= fare_cap]
    if 'trip_miles' in df.columns:
        miles_cap = df['trip_miles'].quantile(0.99)
        df = df[df['trip_miles'] <= miles_cap]

    return df

# Function to save cleaned data back to GCS
def save_cleaned_data_to_gcs(df, output_file_path):
    bucket = client.get_bucket(bucket_name)
    output_blob = bucket.blob(output_file_path)
    output_blob.upload_from_string(df.to_parquet(index=False), content_type="application/octet-stream")
    print(f"Cleaned data saved to {output_file_path}")

# Main function to process all files
def process_files():
    for year in range(2020, 2024):
        for month in range(1, 13):
            file_path = f"{landing_folder}/fhvhv_tripdata_{year}-{month:02}.parquet"
            output_path = f"{cleaned_folder}/fhvhv_tripdata_{year}-{month:02}.parquet"
            try:
                # Load data
                print(f"Processing {file_path}")
                df = load_data_from_gcs(file_path)

                # Clean data
                df_cleaned = clean_data(df)

                # Save cleaned data
                save_cleaned_data_to_gcs(df_cleaned, output_path)
```

```
        except Exception as e:
            print(f"Failed to process {file_path}: {e}")

# Run the processing function
process_files()
```

Appendix D:

```
#importing necessary libraries
from pyspark.sql import SparkSession
from pyspark.sql.functions import unix_timestamp, col
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.regression import LinearRegression
from pyspark.ml.evaluation import RegressionEvaluator

# Initialize Spark session with memory optimization
spark = SparkSession.builder \
    .appName("Taxi Data Batch Processing and Model Training") \
    .config("spark.executor.memory", "8g") \
    .config("spark.executor.cores", "2") \
    .config("spark.executor.instances", "4") \
    .config("spark.speculation", "true") \
    .getOrCreate()

# Input and output paths
input_folder_path = "gs://my-bigdata-project-aa/cleaned/"
trusted_folder_path = "gs://my-bigdata-project-aa/trusted/"
model_folder_path = "gs://my-bigdata-project-aa/models/"

# List of files to process (2020-2023 all months)
file_list = [f"fhvhv_tripdata_{year}-{month:02d}.parquet"
```

```
            for year in range(2020, 2024) for month in range(1, 13)]

# Process files individually
for file_name in file_list:
    print(f"Processing file: {file_name}")
    try:
        # Read file from `cleaned` folder
        file_path = f"{input_folder_path}{file_name}"
        df = spark.read.parquet(file_path)

        # Select relevant columns
        required_columns = [
            "pickup_datetime", "dropoff_datetime", "trip_miles", "tolls",
            "sales_tax", "congestion_surcharge", "tips"
        ]
        df = df.select(*required_columns)

        # Feature engineering: Calculate trip duration
        df = df.withColumn(
            "trip_duration",
            unix_timestamp(col("dropoff_datetime")) - unix_timestamp(col("pickup_datetime"))
        ).drop("pickup_datetime", "dropoff_datetime")

        # Save processed file directly into the `trusted` folder
```

```
        trusted_file_path = f"{trusted_folder_path}{file_name}"
        df.coalesce(1).write.mode("overwrite").parquet(trusted_file_path)
        print(f"Saved processed file to: {trusted_file_path}")

    except Exception as e:
        print(f"Error processing file {file_name}: {e}")
        continue  # Skip to the next file if there's an issue

# Combine all processed files
print("Combining all processed files from the trusted folder...")
try:
    combined_df = spark.read.parquet(f"{trusted_folder_path}*.parquet")
    print("All files combined successfully.")
except Exception as e:
    print(f"Error combining files: {e}")
    exit(1)

# Prepare data for model training
assembler = VectorAssembler(
    inputCols=["trip_miles", "tolls", "sales_tax", "congestion_surcharge", "trip_duration"],
    outputCol="features"
)
combined_df = assembler.transform(combined_df).select("features", "tips")
```

```
# Train-test split
train_data, test_data = combined_df.randomSplit([0.8, 0.2], seed=42)

# Train Linear Regression model
print("Training Linear Regression model...")
lr = LinearRegression(featuresCol="features", labelCol="tips", regParam=0.01)

# Fit the model on training data
model = lr.fit(train_data)

# Save the model
model_path = f"{model_folder_path}taxi_tip_prediction_model"
try:
    model.write().overwrite().save(model_path)
    print(f"Model saved to: {model_path}")
except Exception as e:
    print(f"Error saving the model: {e}")

# Evaluate the model
print("Evaluating the model...")
predictions = model.transform(test_data)

evaluator = RegressionEvaluator(labelCol="tips", predictionCol="prediction")
```

```
mse = evaluator.evaluate(predictions, {evaluator.metricName: "mse"})
mae = evaluator.evaluate(predictions, {evaluator.metricName: "mae"})
r2 = evaluator.evaluate(predictions, {evaluator.metricName: "r2"})

print("Model Evaluation Metrics:")
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R-squared (R2): {r2}")

from pyspark.sql import SparkSession
from pyspark.sql.functions import unix_timestamp, col, hour, dayofweek, month, when
from pyspark.ml import Pipeline
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.regression import LinearRegression
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

# Initialize Spark session
spark = SparkSession.builder \
  .appName("Taxi Data Pipeline with Cross Validation") \
  .config("spark.executor.memory", "8g") \
  .config("spark.executor.cores", "2") \
  .config("spark.executor.instances", "4") \
  .config("spark.speculation", "true") \
```

```
    .getOrCreate()


# Input and output paths

input_folder_path = "gs://my-bigdata-project-aa/cleaned/"

trusted_folder_path = "gs://my-bigdata-project-aa/trusted/"

output_combined_file_path = "gs://my-bigdata-project-aa/cleaned/combined_cleaned_data.parquet"


# Load and preprocess data

print("Loading and preprocessing combined data...")

df = spark.read.parquet(output_combined_file_path)


# Drop observations with extreme outliers for tips, trip distance, and fare

print("Removing outliers...")

df = df.filter((col("tips") >= 1) & (col("tips") <= 50)) \

       .filter((col("trip_miles") >= 0.1) & (col("trip_miles") <= 100)) \

       .filter((col("base_passenger_fare") >= 1) & (col("base_passenger_fare") <= 500))


# Handle skewness by applying log transformations to numeric features

df = df.withColumn("log_trip_miles", when(col("trip_miles") > 0,
col("trip_miles").cast("double")).alias("log_trip_miles")) \

       .withColumn("log_fare", when(col("base_passenger_fare") > 0,
col("base_passenger_fare").cast("double")).alias("log_fare")) \

       .withColumn("log_tips", when(col("tips") > 0, col("tips").cast("double")).alias("log_tips"))


# Define features and target
```

```
features = [
    "log_trip_miles", "tolls", "sales_tax", "congestion_surcharge",
    "airport_fee", "log_fare", "trip_duration",
    "pickup_hour", "pickup_day", "pickup_month"
]
target = "log_tips"

# Assemble features
assembler = VectorAssembler(inputCols=features, outputCol="features")

# Define the Linear Regression model
lr = LinearRegression(featuresCol="features", labelCol=target)

# Build a pipeline
pipeline = Pipeline(stages=[assembler, lr])

# Split data into training and testing sets
train_data, test_data = df.randomSplit([0.8, 0.2], seed=42)

# Cross-Validation setup
paramGrid = ParamGridBuilder() \
    .addGrid(lr.regParam, [0.01, 0.1, 0.5]) \
    .addGrid(lr.elasticNetParam, [0.0, 0.5, 1.0]) \
    .build()
```

```
crossval = CrossValidator(estimator=pipeline,
                          estimatorParamMaps=paramGrid,
                          evaluator=RegressionEvaluator(labelCol=target, predictionCol="prediction", metricName="r2"),
                          numFolds=5)

# Train model with Cross-Validation
print("Training model with Cross-Validation...")
cv_model = crossval.fit(train_data)

# Evaluate model on test data
print("Evaluating model on test data...")
predictions = cv_model.transform(test_data)

evaluator = RegressionEvaluator(labelCol=target, predictionCol="prediction")
mse = evaluator.evaluate(predictions, {evaluator.metricName: "mse"})
mae = evaluator.evaluate(predictions, {evaluator.metricName: "mae"})
r2 = evaluator.evaluate(predictions, {evaluator.metricName: "r2"})

print(f"Evaluation Metrics:\nMean Squared Error (MSE): {mse}\nMean Absolute Error (MAE): {mae}\nR-squared (R2): {r2}")

# Stop Spark session
spark.stop()
```

Appendix E:

```
from pyspark.sql import SparkSession
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Initialize Spark session with increased driver memory and Arrow optimization
spark = SparkSession.builder \
    .appName("Data Visualization for Taxi Tips") \
    .config("spark.driver.maxResultSize", "8g") \
    .getOrCreate()
spark.conf.set("spark.sql.execution.arrow.pyspark.enabled", "true")

# Path to combined data
combined_file_path = "gs://my-bigdata-project-aa/cleaned/combined_cleaned_data.parquet"

# Load the combined data
print("Loading combined data...")
df = spark.read.parquet(combined_file_path)

# Downsample data for visualization
print("Sampling data for visualization...")
sampled_df = df.sample(fraction=0.01, seed=42).toPandas()
```

```
# Define features for analysis
features = [
    "trip_miles", "tolls", "sales_tax", "congestion_surcharge",
    "airport_fee", "base_passenger_fare", "trip_duration",
    "pickup_hour", "pickup_day", "pickup_month"
]

# Placeholder for predicted tips (synthetic data for scatter plot demonstration)
# Replace these with actual model predictions if available
sampled_df["predicted_tips"] = sampled_df["tips"] * 0.9 + (sampled_df["tips"].std() * 0.1)

# Visualization 1: Distribution of Tips (Granular Scale)
plt.figure(figsize=(10, 6))
sns.histplot(sampled_df["tips"], bins=range(0, int(sampled_df["tips"].max()) + 1, 1), kde=False,
color="blue")
plt.title("Distribution of Tips (Granular Scale)")
plt.xlabel("Tip Amount (Rounded to Integers)")
plt.ylabel("Frequency")
plt.xticks(range(0, int(sampled_df["tips"].max()) + 1, 5))  # Adjust x-ticks for better readability
plt.tight_layout()
plt.savefig("tips_distribution_granular.png")
plt.show()

# Visualization 2: Correlation Heatmap
plt.figure(figsize=(12, 8))
```

```
corr_matrix = sampled_df[features + ["tips"]].corr()

sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f", cbar=True)

plt.title("Correlation Heatmap of Features with Tips")

plt.tight_layout()

plt.savefig("correlation_heatmap.png")

plt.show()


# Visualization 3: Relationship Between Base Fare and Tips

plt.figure(figsize=(10, 6))

sns.scatterplot(data=sampled_df, x="base_passenger_fare", y="tips", hue="trip_miles", palette="viridis",
alpha=0.7)

plt.title("Relationship Between Base Fare and Tips (Colored by Trip Miles)")

plt.xlabel("Base Passenger Fare")

plt.ylabel("Tip Amount")

plt.legend(title="Trip Miles")

plt.tight_layout()

plt.savefig("fare_vs_tips.png")

plt.show()


# Visualization 4: Boxplot of Sales Tax vs Tips

plt.figure(figsize=(10, 6))

sns.boxplot(data=sampled_df, x="sales_tax", y="tips")

plt.title("Boxplot of Sales Tax vs Tips")

plt.xlabel("Sales Tax")

plt.ylabel("Tip Amount")
```

```
plt.tight_layout()

plt.savefig("sales_tax_vs_tips_boxplot.png")

plt.show()


# Visualization 5: Predicted vs Actual Tips

plt.figure(figsize=(10, 6))

sns.scatterplot(data=sampled_df, x="tips", y="predicted_tips", alpha=0.7)

plt.plot([0, sampled_df["tips"].max()], [0, sampled_df["tips"].max()], color="red", linestyle="--",
label="Ideal Prediction")

plt.title("Predicted vs Actual Tips")

plt.xlabel("Actual Tips")

plt.ylabel("Predicted Tips")

plt.legend()

plt.tight_layout()

plt.savefig("predicted_vs_actual_tips.png")

plt.show()


# Visualization 6: Feature Coefficients Bar Graph

# Placeholder coefficients (replace with model's actual coefficients if available)

coefficients = {

    "trip_miles": -0.072, "tolls": 0.051, "sales_tax": 0.041, "congestion_surcharge": 0.137,

    "airport_fee": 0.528, "base_passenger_fare": 0.053, "trip_duration": -0.00006,

    "pickup_hour": 0.0039, "pickup_day": 0.0006, "pickup_month": 0.0037

}
```

```
coefficients_df = pd.DataFrame({
    "Feature": list(coefficients.keys()),
    "Coefficient": list(coefficients.values())
}).sort_values(by="Coefficient", key=abs, ascending=False)

plt.figure(figsize=(12, 6))
sns.barplot(data=coefficients_df, x="Coefficient", y="Feature", palette="coolwarm")
plt.title("Feature Coefficients (Sorted by Absolute Value)")
plt.xlabel("Coefficient Value")
plt.ylabel("Feature")
plt.tight_layout()
plt.savefig("feature_coefficients.png")
plt.show()

print("All visualizations have been saved successfully!")
```